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Application of artificial intelligence to predict flow assisted corrosion in nuclear/thermal power plant

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Flow assisted corrosion (FAC) is a wall-thinning phenomena of carbon steel pipe in nuclear and thermal power plant. Due to FAC, many accidents have taken place in nuclear plants resulting in casualties. In FAC, dissolution of iron from the iron-oxide fluid interface at pipe wall takes place and it is affected by *p*H, oxygen concentration, flow rate, temperature and chromium content of piping material. Due to complex interaction of these parameters, FAC prediction is difficult using conventional modeling tools and experimental evaluation is time consuming and costly. In this work, artificial neural network (ANN) has been used for FAC prediction using 320 data points collected from published literature. The neural network training was carried out using Lavender-Marquardt back-propagation algorithm in Matlab. The results show that ANN is a powerful tool for predicting FAC rate with regression coefficient above 90% and hence it can be very useful by regular training of the model with actual operational data in safety management and long term planning in nuclear/thermal power plant. A sensitivity analysis with respect to each parameter has been carried out using ANN model. It is observed that FAC rate is lower under alkaline conditions and goes through a maxima in a temperature range of 140 to 150°C.

Keywords: Artificial Neural Network, Flow Assisted Corrosion, % chromium, flow velocity, pH, oxygen concentration

Flow assisted corrosion (FAC) is a wall thinning phenomena of low alloy steel pipe in nuclear and thermal power plant due to high temperature and pressure condition. FAC leads to wall thinning of pipeline network/pipe fittings through material loss which result in frequent break-down or accidents leading to injuries and fatalities. FAC related accidents[1] have taken place at Surry (1986) (rupture of elbow), Arkansas (1986) (drain extraction line), Milstone (1991) (rupture of elbow), Mihama (2004) (feedwater line), Balakovo (2004) (feed water bypass line). These conditions are found in secondary circuits of pressurized water, feed water system, two phase flow in boiling water reactor. FAC is dissolution dominant process and it strongly depends upon dissolved oxygen (DO) in water, pH, velocity, temperature, alloy content in piping material and geometric factor[1-8]. FAC occurs in both single as well as two phase flow but it requires high temperature which is > 95°C[9]. For constant mass flow rate, steam quality and water chemistry, the maximum FAC rate found at 140°C[9]. But this temperature is according to laboratory data, the actual FAC failure occur above this derived maximum. Flow rate of the liquid has been found to have a linear effect on the FAC rate. Under flowing conditions, a potential difference is created between the liquid and piping material which result in dissolution of protective oxide (magnetite) layer into the protective stream. Rapid removal of magnetite layer is promoted by neutral or slightly alkaline water. FAC rate is found to decrease with the *p*H in the range 5 to 10. In order to control FAC rate *p*H needs to be maintained between 9.2-9.7. The concentration of dissolved oxygen has significant impact on FAC rate. The material of construction of piping material having 0.1% chromium or molybdenum can help in lowing FAC rate. It is also observed that FAC rates are higher in the downstream component of flow restricted or redirected device like orifice, elbow, reducer, T-junction and valves[9-11].

Different models have been developed for prediction of FAC[10-13]. The classification of these models are based on empirical models and mechanistic models. Kastner and Chexwal-Horowitz are empirical models while Sanchez-caldera and Bingold are mechanistic models. In Kastner model, FAC rate is depends upon velocity, temperature, alloy content, pH, oxygen content and water quality. The

Kastner model %Cr and Mo content in piping material consider as single component. This model is basis for commercial WALTEC code. Chexal Horowitz model has been used in development of CHECWORKS code which considers FAC ratedepends on temperature, pH, alloy content, oxygen concentration in flowing fluid, geometric factor. In this model, % of Cr and Mo consider separately. Sanchez-caldera and Bignold model consider FAC rate as a function of pH, velocity and geometric factor. In Sanchez-caldera model, temperature dependency is considered by Arrhenius equation. Various agencies (Areva, CHECKWORKS etc) have created consortium to collect wall thinning data from various nuclear power plants and this database is used to refine the FAC models.

FAC can also be termed as solid-liquid mass transfer process. The mass transfer of oxide layer in water can be expressed in terms of Sherwood number (Sh) = kd/*D* where k is mass transfer coefficient. d = tube diameter, *D* is the ferrous ion diffusion coefficient in water. Literature contains information related to FAC in various forms such as wall thinning rate in mm/year or mass transfer coefficient in (mm/s). All the nuclear power plants regularly collect wall thinning rate at regular interval, however data is not available in public domain. Artificial neural network (ANN) technique can be used to relate the various parameters discussed above with FAC rate. We have developed a graphical user interface based tool for compilation of FAC data in nuclear power plant and thermal power plants. The ANN based approach has been demonstrated using the available experimental data from literature for regression analysis and sensitivity analysis with respect to each parameter using ANN model.

Experiment Section

Artificial Neural Network (ANN) originally motivated by looking at machines which replicates the brain functionality hence it is an integral part of artificial intelligence with the assumption is that brain has single learning algorithm[14]. ANN technique is widely used in predication, control system, classification and optimization problem. Our brain is full of neurons and it has input wires called dendrites and output wires called Axon. It is like a computational unit which takes input, cell body of neurons process on it and send the output. ANN consists of three layers: input layer, hidden layer and output layer. Each layer consists of number of neurons. For input layer number of neurons depending upon number of independent variable in the dataset while for output layer number of neurons is equal to number of output layer and thus it form highly complex network. Number hidden layer and neurons in hidden layer where actual computation of polynomial takes place. First computation of activation on hidden units based on input and inputs weights and activation of output is calculated by hidden layer activation and second layer weights. ANN uses empirical risk minimization technique to minimize the error in training data. Activation in hidden layer calculated as

$$hi= f(\mathrm{Wi} \times \mathrm{Xi}) \quad ...(1)$$

where Wi=weight on each edge, Xi =value from input layer and f=is activation function

The activation function can be vary from user to user it may be Linear, Symmetric–Saturatinglinear, Log Sigmoid, Tan Sigmoid, Radial basis.

The performance of the ANN model is evaluated in terms of Mean Square Error (Eq. 2)

$$MSE = \frac{1}{N}\left(\sum_{i=1}^{n} (Yi - \tilde{\mathrm{Y}})^{2} \right) \quad ...(2)$$

where N is the size of sampled data, and Y_i ,Ỹi,arethe actual value, predicted value and the meanvalue, respectively.

Coefficient of Correlation:

$$R = \frac{\mathrm{cov}(Y, \tilde{\mathrm{Y}}}{\sqrt{\mathrm{cov}(\mathrm{Y},\mathrm{Y}) \times \mathrm{cov}(\tilde{\mathrm{Y}}\ \ , \tilde{\mathrm{Y}}\ \ )}} \quad ...(3)$$

where

$$COV(Y, \tilde{\mathrm{Y}}) = \sqrt{\frac{1}{(N-1)}} \sum_{1}^{N} (Y - (\overline{\tilde{\mathrm{Y}}}))(\mathrm{Y} - \tilde{\mathrm{Y}}) \quad ...(4)$$

R is a simple statistical parameter which reveals how good the model fits the data andconsequently, expresses the applicability of the model. The closer the value of R approaches 1, the better the model predict the data.

Building a neural network is an experimental work and the major difficulty involved in obtaining optimal network. The present work focuses on data driven modeling of mass transfer coefficient for FAC using ANN. The FAC data required for Artificial Neural Network is obtained from open literature and data points have been obtained from graphs with the help of plot digitizer software. The published literature data were screened for incompleteness, redundancies, and evident inaccuracies and finally 320 data points were collected for ANN modeling[15-21]. Table 1 contains range of collected data set for FAC predication. The raw dataset used for ANN modeling is provided in Table S1 in the supporting information.ANN model has been developed for FAC rate, mm/year as output parameter and input parameters were pH, temperature (^{o}C), dissolved oxygenin flowing fluid (ppb), Cr % in piping material, and flow velocity (m/s). Different neural network configurations were created using Matlab ANN toolbox. These configurations were based on number of neurons in hidden unit and percentage split of data for training, testing and validation. Topology of three layered feed forward neural network is shown in Fig.1.

Results and Discussion

ANN regression analysis

Various configurations in terms of division of training, testing, validation data and number of hidden layer have been studied. Optimal configuration was obtained with three hidden layers. 60% of the data was used for training, 20% data was used for validation and remaining 20% data was use for model testing. ANN results were evaluated based on R^2 value. For optimal configuration, R value were observed to be 0.89, 0.96 and 0.91 for training, validation and testing, respectively (Fig. 2). Hence this model is used for sensitivity analysis with respect to each parameter.

Table 1—Range of input and output parameters for ANN modeling

Sr. No.	Parameter	Range
1	Temperature (^{o}C)	27 - 247
2	*p*H	3.77 - 10.4
3	Fluid velocity (m/s)	0 - 56
4	Dissolved oxygen (ppb)	0 - 1200
5	% Cr	0.001-18.32

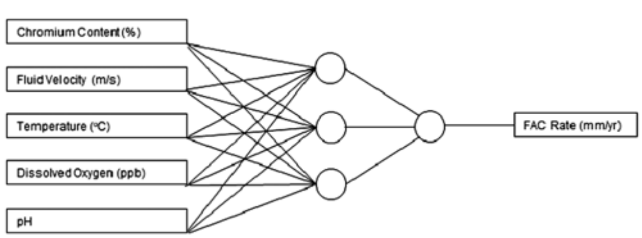

Fig. 1— Topology of three layered feed forward neural network

ANN prediction

In order to understand the efficacy of trained ANN model, a sensitivity analysis has been carried out with respect to effect of Chromium content, DO, *p*H, temperature and fluid velocity. Effect of *p*H with each parameter has been reported for value of 7 and 9 as it is well established in the literature that in alkaline condition FAC rate is significantly smaller compared to neutral condition. Figure 3A shows the effect of Cr content (%) on FAC rate at velocity = 25 m/s, T = 140°C and DO = 5 ppb. It is observed that at *p*H = 7, FAC rate reduces with increase in % Cr and almost constant beyond % Cr = 2. The FAC rate at *p*H = 9 was almost an order of magnitude lower than the *p*H = 7. At *p*H of 9, the FAC rate goes through a maxima at % Cr= 1.32.

Effect of DO has been studied in the range of 0 to 100 ppb at *p*H of 7 and 9 and velocity = 25 m/s, T = 140°C and Cr content = 0.1% (Fig. 3B).For a DO change from 0 to 100 ppb at *p*H = 7, the FAC rate changes from 26 mm/yr to 2.2 mm/yr (about 1000% variation), whereas at a *p*H of 9, the variation is from 0.96 to 0.83 mm/yr (15% variation).Fig. 4 shows the effect of *p*H at T of 140 and 180°C and velocity = 25 m/s and Cr content = 0.1%. Maxima in FAC rate is observed in acidic and neutral conditions and significantly drops under alkaline conditions.

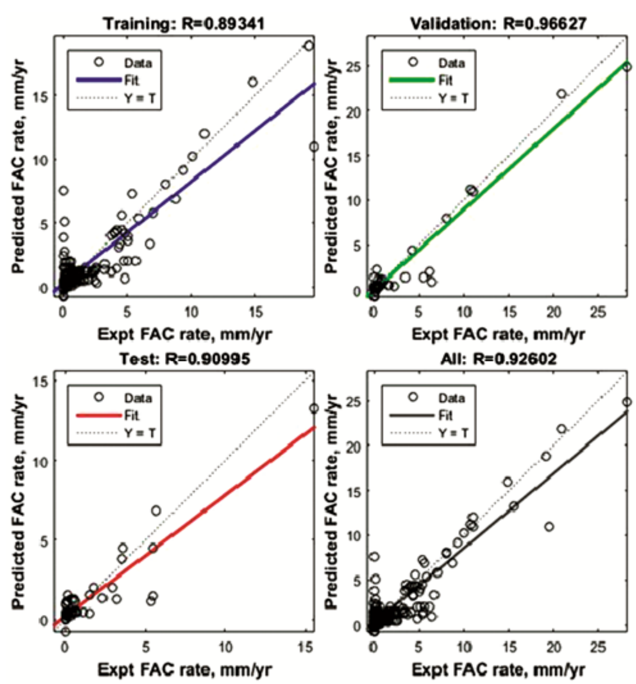

Fig. 2 — Parity plot for training, validation and testing of FAC data

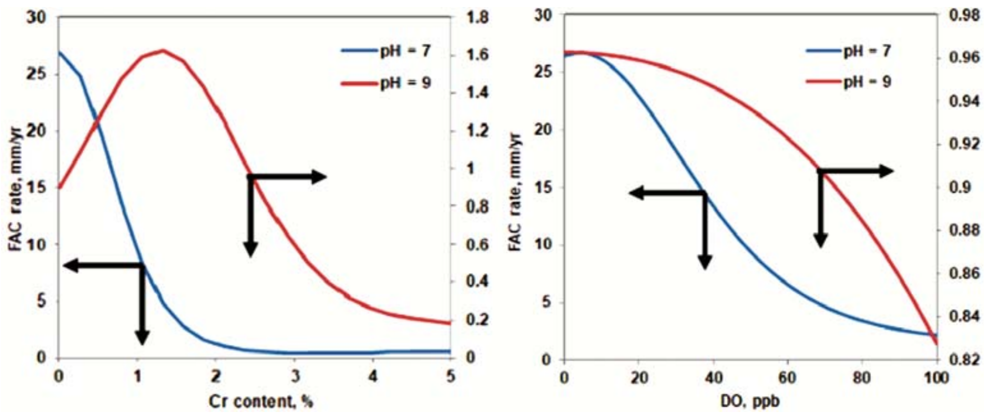

Fig. 3 — (A) Effect of Cr content (%) on FAC rate (a) *p*H = 7 (b) *p*H = 9 based on ANN model(velocity = 25 m/s, T = 140°C and DO = 5 ppb) and (B) Effect of dissolved oxygen (DO) on FAC rate (a) *p*H = 7 (b) *p*H = 9 based on ANN model(velocity = 25 m/s, T = 140°C and Cr content = 0.1%)

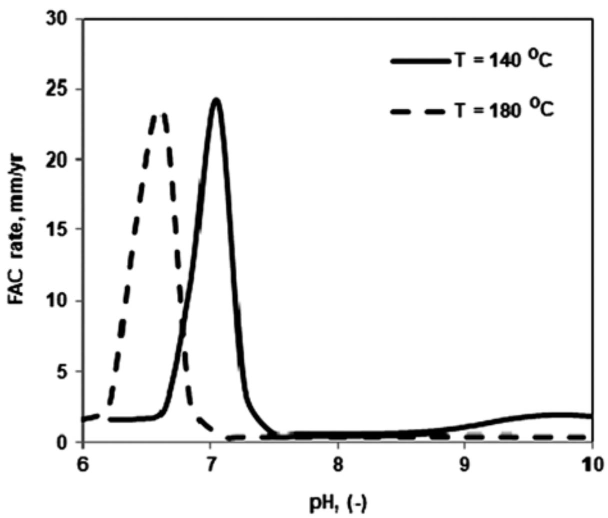

Fig. 4 — Effect of *p*H on FAC rate at temperature = 140°C and 180°C based on ANN model(velocity = 25 m/s, DO = 5 ppb and Cr content = 0.1%)

The FAC rate is higher at 140°C compared to 180°C throughout the *p*H range. Effect of temperature has been shown in Fig. 5A at velocity = 25 m/s, DO = 5 ppb and Cr content = 0.1%. It is observed that FAC rate goes through a maxima in temperature range of 120 to 140°**C**. The location of maxima is found to depend on the *p*H. FAC rate is significantly low below temperature of 80°C and above 170°C. The effect of velocity (in the range of 0 to 40 m/s) on FAC rate at DO = 5 ppb, temperature = 140°C and Cr content = 0.1% is shown in Fig. 5B. FAC rate increases with approximate quadratic nature with velocity. Under alkaline condition, FAC rate is significantly lower than neutral condition throughout the velocity range.Hence the

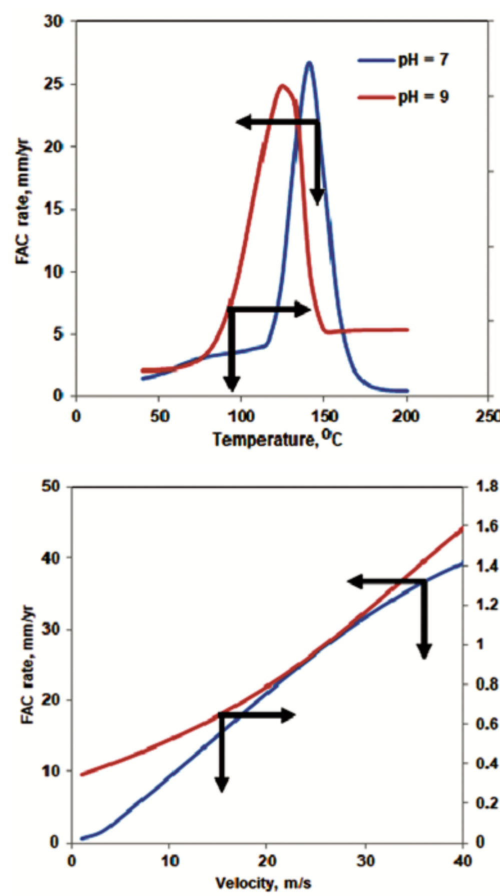

Fig. 5 — (A) Effect of temperature on FAC rate at (a) *p*H = 7 (b) *p*H = 9 based on ANN model(velocity = 25 m/s, DO = 5 ppb and Cr content = 0.1%) and (B) Effect of velocity on FAC rate at (a) *p*H = 7 (b) *p*H = 9 based on ANN model (DO = 5 ppb, temperature = 140°C and Cr content = 0.1%)

NPPs operate the primary and secondary cooling systems under alkaline *p*H conditions with controlled dissolved oxygen.

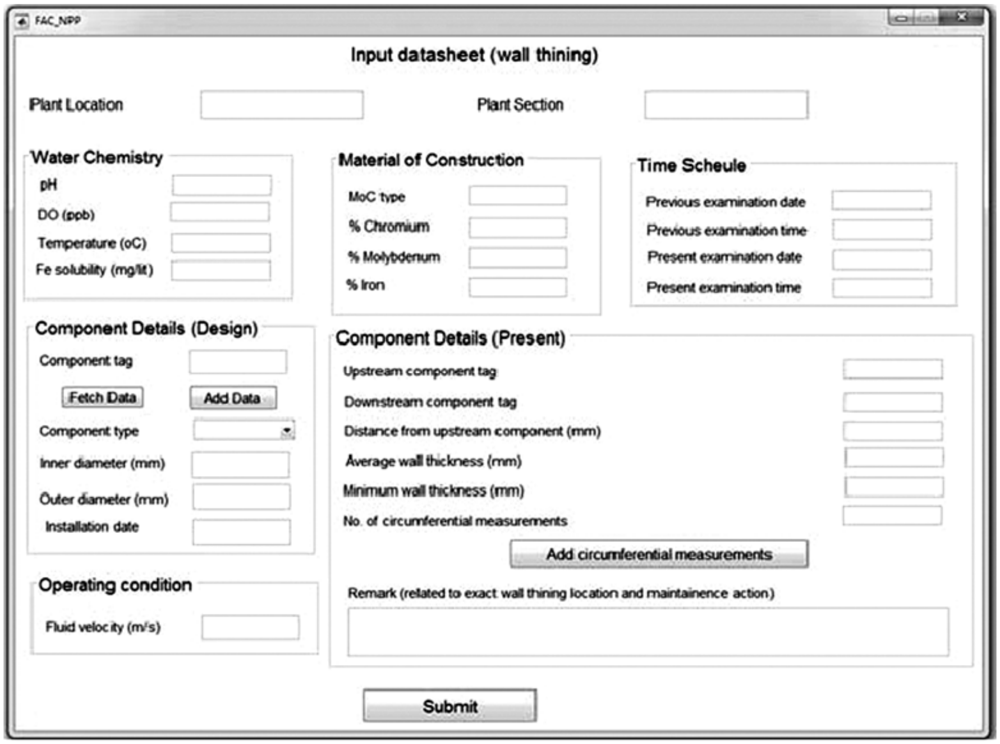

Fig. 6 — Graphical user interface for data collection related to flow assisted erosion-corrosion from thermal/nuclear power plants

Graphical user interface for collection of wall thinning data

ANN is a very powerful tool which can account for the complexity in the prediction of FAC rate based on various parameters such as *p*H, DO, %Cr, temperature and fluid velocity. However, it still does not account for the geometric effects such as type of pipe fittings, valves, effect of flow complexity in downstream component due to upstream component[22,23]. If we take an example of elbow, the effect of FAC on intrados and extrados is significantly different. In order to account for these effects, wall thickness measurement at different downstream distances and along the entire periphery is carried out in NPP at regular interval[24]. This data is used to decide the frequency of component replacement and minor changes in piping network to reduce the potential accidental hazards. In this work, a graphical user interface (GUI) based data input tool has been developed (Fig. 6). In this GUI, user can input, the plant location, component details, water chemistry, MoC details, date and time of measurement, exact location of measurement from upstream components, details measurements in circumferential direction etc. This data is saved in spreadsheet format and can be subjected to similar ANN based analysis. In every campaign, significant numbers of data points get added in the database and strengthen the prediction. This approach will help to reduce the risk of FAC related accidents and help to design the piping networks in efficient manner.

Conclusion

The flow assisted corrosion (FAC) is one of the important factors in the safe operation of primary and secondary heat transfer networks in nuclear and thermal power plants. The present work deals with FAC predication by using ANN tool. ANN helps to predict the mutual effect of the factor affecting the FAC. The sensitivity analysis using ANN predictive model captures almost all the observations reported in the literature. Result obtained from ANN modeling indicates that consistent monitoring of piping system in nuclear and thermal power plant and generated data feed to neural network will provide robust technique for safety management and thus avoid accidents and other health hazard in nuclear and thermal power plant.

Nomenclature

d	pipe diameter, m
R	Regression coefficient, -
Sh	Sherwood number, -

Abbreviations

ANN Artificial neural network
COV Coefficient of variation
DO Dissolved oxygen, ppb
FAC Flow assisted corrosion
GUI Graphical user interface
MoC Material of construction

References

1 Ahmed W H, *Nuclear Power: practical aspects*, Ahmed W H (Ed.), InTech publication, (2012) 153.
2 Poulson B, *Int J of Nuclear Energy*, (2014) 1.
3 Kim I S, Van Der Halm M & Ballinger R G, *J Korean Nucl Soc*, 30 (1998) 148.
4 Remy F N &Bouchacourt M, *NuclEng Des*, 133 (1992) 23.
5 Kain V, Roychowdhury S, Mathew T &Bhandakkar A, *J Nucl Mater*, 383 (2008) 86.
6 Uchid S, Naitoh M, Okada H, Uehara Y &Koshizuka S, *NuclEng Des*, 241 (2011) 4585.
7 Madasamy P, Subramanian H, Krishna Mohan T V, Velmurugan S, Natarajan E & Narasimhan S V, *Corros Eng Sci Tech*, 46 (2011) 346.
8 Pietralik J M, *E-Journal of Advanced Maintenance*, 4 (2012) 63.
9 Chexal, V.K., *CHECWORKS^{TM} Computer Program User's Manual*, TR-103496, 1993.
10 Kastner W, Erve M, Henzel N & Stellwag B, *NuclEng Des*, 119 (1990) 431.
11 Poulson B, *Wear*, 233 (1999) 497.
12 Chexal B, *EPRI NSAC-202L-R2* (1999).
13 Yoneda K, Morita R, Fujiwara K & Inada F, *ASME PVP Conference, Paris*, 97601 (2013).
14 Demuth H & Beale M,*Neural Network Toolbox for use with Matlab, The Mathwork Version*, 4, (2002)
15 Fujiwara K, Yoneda K & Inada F, *20th International corrosion congress and process safety congress*, 2017, paper 78701.
16 Kastner W, Erve M, Henzel N & Stellwag B, *Int Atom Ener Agency Report, IWGRRPC*, 88- (1990) 49.
17 Dooley R B, *Power Plant Chem*, 10 (2008) 68.
18 Lister D H, Liu L, Feicht A, Khatibi M, Cook W, Fujiwara K, Kadoi E, Ohira T, Takiguchi H & Uchida S, *Power Plant Chem*,10 (2008) 659.
19 Watanabe Y, Abe H & Abe H, *Proceedings of the ASME 2010 Pressure Vessels & Piping Division / K-PVP Conference PVP,* (2010) 1.
20 Poulson B & Chexal B, *Br Corros J*, 26 (1991) 183.
21 Fujiwara K, Domae M, Yoneda K, Inada F, Ohira T & Hisamune K, *NuclEng Des*, 241 (2011) 4482.
22 Ahmed W H, Bello M M, Nakla M E & Sarkhi A A, *NuclEng Des*, 252 (2012) 52.
23 Fouad M A, Zewail T M, Amine N K & El-Taweel Y A, *Int J Eng Adv Tech*, 2 (2013) 36.
24 Trevin S & Moutrille M P, *18th World Conference on Nondestructive Testing, Durban, South Africa*, (2012) 1.